Structural Vibration Control Based on MISSA-BP Algorithm and Finite State Feedback

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Abstract

To address the problems that the sparrow search algorithm is prone to falling into local optima during the search process and still has room for improvement in convergence speed, the active control performance of traditional BP neural networks is unstable, and arranging sensors on all floors is poor in economy and practicality, a multi-strategy improved sparrow search algorithm (MISSA) is proposed, and 5 benchmark test functions are selected for performance evaluation. MISSA is combined with a BP neural network to design the MISSA-BP algorithm, which synchronously optimizes the number and locations of sensors and the corresponding BP neural network, and vibration control is performed on a 20-story Benchmark model under the action of 2 types of seismic waves. The results show that MISSA has better optimization accuracy and speed, as well as stronger exploration capability; the MISSA-BP algorithm achieves better control performance than a BP neural network with superior training performance. The algorithm requires only the displacement and velocity information fed back by sensors on 7 floors to achieve a control effect close to that of full-state feedback LQR control, and it also has a certain generalization ability.

Full Text

Structural Vibration Control Based on MISSA-BP Algorithm and Finite State Feedback

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Abstract: In response to the problems that the sparrow search algorithm is prone to falling into local optima during the search process and still has room for improvement in convergence speed, that the active control effect of traditional BP neural networks is unstable, and that installing sensors on all floors is poor in economy and practicality, a multi-strategy improved sparrow search algorithm (MISSA) is proposed, and five benchmark test functions are selected for performance evaluation. The MISSA is combined with a BP neural network to design the MISSA-BP algorithm, which synchronously optimizes the number and locations of sensors and the corresponding BP neural network, and vibration control is performed on a 20-story Benchmark model under the action of two types of seismic waves. The results show that MISSA has better optimization accuracy and speed, as well as stronger exploration capability; the MISSA-BP algorithm has better control performance than a BP neural network with better training results; and the algorithm can achieve a control effect close to that of full-state-feedback LQR control using only displacement and velocity information fed back from seven floor sensors, while also possessing a certain generalization capability.

Keywords: finite state feedback; improved sparrow search algorithm; BP neural network; sensors

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Abstract: In response to the problems of being easily trapped in local areas and having room for improvement in convergence speed during the search process of the sparrow search algorithm, the unstable active control effect of traditional BP neural networks, and the poor economy and practicality of arranging sensors on all floors, a multi-strategy improved sparrow search algorithm (MISSA) is proposed, and five benchmark test functions are selected for performance evaluation. Then the MISSA-BP algorithm was designed by combining MISSA with BP neural network. The number and position of sensors and their corresponding BP neural network were synchronously optimized, and vibration control was performed on the 20 layer Benchmark model under the action of two types of seismic waves. The results indicate that MISSA has superior

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optimization accuracy and speed, as well as stronger exploration ability. Additionally, the MISSA-BP algorithm exhibits better control performance than the BP neural network with improved training performance. This algorithm requires feedback solely on displacement and velocity information from seven floor sensors to achieve control effects similar to full-state feedback LQR control, and it also demonstrates a certain degree of generalization ability.

Key words: finite state feedback; improved sparrow search algorithm; BP neural network; sensor

At present, in the field of active vibration control of building structures, traditional control algorithms have achieved many results. However, the mathematical models of traditional methods are difficult to establish, and in practical control there is a time-delay phenomenon, resulting in unstable actual control effects and poor adaptability to changes in the external environment. At the same time, too many sensors increase the hardware cost of the control system, increase the time required for the processor to process feedback information, and also increase the risk of hardware failure.

The sparrow search algorithm (sparrow search algorithm, SSA) was proposed by Xue et al. in 2020

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. Although SSA has a simpler structure, fewer parameters, and higher solution accuracy than other algorithms, it still has shortcomings. Some researchers have made local improvements to SSA. For example, Lü Xin et al.

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proposed a chaotic sparrow search optimization algorithm, and Mao Qinghua et al.

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improved the sparrow search algorithm in multiple ways. The results show that these improved methods increase the diversity of solutions and improve the optimization effect.

With the improvement of information technology, more and more intelligent algorithms have been applied in the field of intelligent structural vibration control, such as neural network algorithms. Neural networks have simple structures and powerful data-processing capabilities, and their network structures can establish nonlinear relationships among complex data. In recent years, certain research results have been achieved in active vibration control of structures

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. Wang Quan et al.

$5-6$

studied decentralized neural-network control of high-rise structures under earthquake action; Pan Zhaodong et al.

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applied an adaptive RBF neural-network algorithm to stepwise decentralized control of building structures; and Wang Zhiwei et al.

8

applied BP neural networks to fuzzy control of structural vibration modes. The results show that neural networks can be effectively applied in the field of structural vibration control. The present study selects a BP neural network, but the training results of a single BP neural network, whose initial parameters are randomly selected, are uncertain and difficult to incorporate into a closed-loop control system. Only by substituting a trained BP neural network into the control system can the calculation of the control force be completed; however, its flexibility is poor and it is not suitable for complex and variable practical engineering. In addition, good BP neural-network training performance is not equivalent to good prediction performance, i.e., good control performance. In structural vibration control, stable and strongly adaptive control algorithms are required.

Because the application of a single BP neural network in structural vibration control has limitations, in recent years scholars have combined optimization algorithms with BP neural networks for application in active structural control. Wang Wen

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combined a genetic algorithm with a BP neural network for sensor optimization and structural vibration control. The results show that it can effectively solve the problems existing in BP neural networks in active structural control. However, no improved sparrow search algorithm with better performance has yet been applied to the synchronous optimization of BP neural networks and sensor placement in vibration control of high-rise structures.

To address the shortcomings of SSA, this study designs a multi-strategy improved sparrow search algorithm (multi-strategy improved sparrow search algorithm, MISSA). First, during population initialization, a Circle chaotic map

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is introduced so that the initial population is distributed more extensively and uniformly throughout the solution space. Second, a sine–cosine algorithm strategy

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is added to the discoverer position-update formula, which helps global optimization in the early stage and local optimization in the later stage. Finally, the Lévy flight strategy

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is introduced into the joiner position-update formula to achieve random search and help obtain the global optimal solution.

To address the poor economic practicability of arranging sensors on all floors, as well as the deficiencies of BP neural networks in active structural vibration control, MISSA is combined with a BP neural network to form the MISSA-BP algorithm. This algorithm can not only optimize the number (limited state feedback) and positions of sensors in the structure, but also select a BP neural network with better practical control performance, thereby reducing the cost of sensors and the processing cost of information processors. At the same time, it overcomes the drawbacks of poor stability and strong randomness of BP neural networks in active control.

1 Basic theory of limited state feedback

Limited state feedback is relative to full-state feedback; that is, sensors are arranged on some degrees of freedom of the structure to feed back the dynamic response information of the structure. Generally speaking, when the control algorithm is the same, because the information obtained through full-state feedback is more comprehensive, the control force calculated by the algorithm using full-state feedback is more reasonable. Therefore, to complete the calculation of control force under limited state feedback, a more reasonable algorithm must be designed; that is, a reasonable control force is calculated using limited feedback information.

The vibration-control algorithm in this study is based on the theory of limited state feedback. First, the number of sensors is determined. Then, sensors are arranged on some floors of the structure to feed back their displacement and velocity under earthquake action. Through the designed algorithm, the control forces that should be applied to all floors are calculated, thereby achieving the purpose of structural vibration control under limited state feedback conditions.

2 Multi-Strategy Improved Sparrow Search Algorithm (MISSA)

SSA divides the sparrow population according to behavior into discoverers, joiners, and randomly selects 10%-20% of the population as sentinels. Although SSA has obvious advantages over other algorithms, it still has shortcomings. To address these drawbacks, a multi-strategy improved sparrow search algorithm that improves both the population initialization and the iteration process is proposed. The specific improvement measures are as follows.

2.1 Improved Circle Chaotic Mapping for Population Initialization

When initializing the sparrow population, if the positions of sparrow individuals in each dimension are generated randomly, individuals tend to cluster in

Fig. 1 Improved Circle chaos mapping before and after improvement

Figure 1: Fig. 1 Improved Circle chaos mapping before and after improvement

local positions. Therefore, Circle chaotic mapping is introduced to disperse the population. Before parameter improvement, its expression is

$$X_{k+1} = \mathrm{mod}\left[X_k + 0.2 - \left(\frac{0.5}{2\pi}\right)\sin(2\pi X_k), 1\right] \qquad (1)$$

After parameter improvement, the expression is

$$X_{k+1} = \mathrm{mod}\left[d_1 X_k + d_2 - \left(\frac{d_3}{d_1 \pi}\right)\sin(d_1 \pi X_k), 1\right] \qquad (2)$$

where: mod is the modulo function; k is the dimension of the solution; d_1, d_2, d_3 are parameters. In this study, the parameter settings[^10] are $d_1 = 4.0$, $d_2 = 0.4$, and $d_3 = 0.7$. Taking $k = 2000$, the comparison of Circle chaotic mapping before and after improvement is shown in Fig. 1. Among them, the distribution diagrams of Circle chaotic mapping before and after improvement are shown in Fig. 1(a) and Fig. 1(b), respectively; the histograms of Circle chaotic mapping before and after improvement are shown in Fig. 1(c) and Fig. 1(d), respectively.

Fig. 1 Improved Circle chaos mapping before and after improvement

From Fig. 1, it can be seen that before improvement, more solutions are concentrated in the interval $[0.2, 0.5]$. The chaotic sequence generated by the improved Circle chaotic mapping is more uniform, and its distribution over the entire value range is broader.

2.2 Improvement of the Discoverer Position Update

In this study, an adaptive sine–cosine strategy is incorporated into the position update process of the discoverers. In the discoverer update formula of SSA, when $R_2 < S_T$, the search range decreases during the iteration process, making it easy to fall into a local optimum; thus, the generated solution is a local optimal solution. To avoid this problem as much as possible, the sine–cosine algorithm[^11] is used for reference, and a nonlinear decreasing factor ω is introduced. The calculation formula for ω and the improved discoverer update formula are

$$\omega = \omega_{\min} + (\omega_{\max} - \omega_{\min}) \cdot \sin(t\pi / T_{\max}) \qquad (3)$$

$$X_{i,j}^{t+1} = \begin{cases} (1-\omega) \cdot X_{i,j}^t + \omega \cdot \sin(r_1) \cdot \left| r_2 \cdot X_{\text{best}} - X_{i,j}^t \right|, & R_2 < S_T \\ (1-\omega) \cdot X_{i,j}^t + \omega \cdot \cos(r_1) \cdot \left| r_2 \cdot X_{\text{best}} - X_{i,j}^t \right|, & R_2 \geq S_T \end{cases} \qquad (4)$$

Here, $\omega_{\min}$ is 0.2; $\omega_{\max}$ is 1; t is the number of iterations; $T_{\max}$ is the maximum number of iterations; $X_{i,j}^t$ is the position of the i-th sparrow in the j-th dimension at generation t; X_{best} is the global optimal position; r_1 is a random number in $[0, 2\pi]$; r_2 is a random number in $[0, 2]$; $R_2 \in [0, 1]$ is the warning value; $S_T \in [0.5, 1]$ is the safety value; and $R_2 < S_T$ indicates safety.

2.3 Improvement of the joiner position update

This study adopts the Lévy flight strategy to improve the update of the joiner positions. This strategy is a random-walk process. Under this mode, sparrow individuals search for food over a relatively large range with a relatively high probability and have strong uncertainty. The idea is to first randomly generate an individual, and then update the position of each individual according to the position of the previous individual. When the discoverer' s fitness value changes little within a certain number of iterations, the Lévy flight strategy is adopted to enhance the exploration capability in the entire search space. The Lévy flight strategy[^12] is determined by Eq. (5), namely

$$F_{\text{Lévy}}(x) = 0.01 \times \frac{r_3 \times \sigma}{|r_4|^{1/\xi}} \qquad (5)$$

where r_3 and r_4 are both random numbers in $[0, 1]$; ξ is taken as 1.5; and σ is

$$\sigma = \left\{ \frac{\Gamma(1+\xi) \times \sin(\pi\xi/2)}{\Gamma[(1+\xi)/2] \times \xi \times 2^{(\xi-1)/2}} \right\}^{1/\xi} \qquad (6)$$

where $\Gamma(x) = (x-1)!$.

Thus, the improved joiner position update is

$$X_{i,j}^{t+1} = \begin{cases} Q \cdot \exp\left(\dfrac{X_{\text{worst}}^t - X_{i,j}^t}{i^2} \right), & i > N/2 \\ X_{\text{p}}^{t+1} + X_{\text{p}}^{t+1} \cdot F_{\text{Lévy}}(d), & \text{other} \end{cases} \qquad (7)$$

where X_{worst}^t is the current worst position; X_{p}^{t+1} is the better position found; Q is a random number following a normal distribution; and d is the variable dimension.

2.4 Update of the alerter position

Alerters can detect danger and transmit warning information to other sparrow individuals. Their position update formula is

$$X_{i,j}^{t+1} = \begin{cases} X_{\text{best}}^{t} + \beta \cdot \left| X_{i,j}^{t} - X_{\text{best}}^{t} \right|, & f_i > f_g \\ X_{i,j}^{t} + K \cdot \left(\dfrac{\left| X_{i,j}^{t} - X_{\text{worst}}^{t} \right|}{(f_i - f_w) + \varepsilon} \right), & f_i = f_g \end{cases} \tag{8}$$

where X_{best}^{t} is the current global best position; β is a normally distributed random number with mean 0 and variance 1; $K \in [-1, 1]$ is a random number; f_i is the fitness value of the i-th individual; f_g and f_w are the best and worst fitness values, respectively; and ε is an extremely small constant to ensure that the formula is meaningful.

3 Algorithm performance evaluation

The algorithm in this study was programmed on a PC with the following parameters: i5-7300HQ CPU @ 2.5 GHz, onboard RAM of 16.0 GB, Windows 10 operating system, and Matlab R2019b programming software. The information on the benchmark test functions used is shown in Table 1. F1–F3 are standard unimodal test functions, used to test the convergence speed and accuracy of the algorithm. F4–F5 are standard multimodal test functions, used to evaluate the global search and local development capabilities of the algorithm. To demonstrate the superiority of MISSA, the test results of the genetic algorithm (GA), particle swarm optimization (PSO), whale optimization algorithm (WOA), and basic sparrow search algorithm (SSA) are compared with it. The parameter settings of each algorithm are shown in Table 2. To fully illustrate the effectiveness of the improvement and reduce randomness, each algorithm was run 30 times on each test function, the population size was set to 50, and the maximum number of iterations was set to 500. The test iteration curves of each algorithm are shown in Fig. 2.

Table 1 Benchmark test functions

Function	Type	Value range	Optimal solution
F1 (30 dimensions)	Sphere	$[-100, 100]$	0
F2 (50 dimensions)	Schwefel' s 2.22	$[-10, 10]$	0
F3 (100 dimensions)	Schwefel' s 1.2	$[-100, 100]$	0
F4 (30 dimensions)	Rastrigin	$[-5.12, 5.12]$	0
F5 (50 dimensions)	Ackley	$[-32, 32]$	0

Table 2 Parameter settings for each algorithm

Algorithm type	Parameter settings
GA	Crossover probability $P_c = 0.9$, mutation probability $P_m = 0.09$
PSO[^13]	$C_1 = 2$, $C_2 = 2$, $\omega_{\min} = 0.4$, $\omega_{\max} = 0.9$
WOA[^14]	a decreases linearly from 2 to 0, $b = 1$
SSA[^3]	Discoverer proportion PD is 0.2, alerter proportion SD is 0.1, $R_2 = 0.8$
MISSA[^3]	Discoverer proportion PD is 0.2, alerter proportion SD is 0.1, $\omega_{\min} = 0.5$, $\omega_{\max} = 1$, $R_2 = 0.8$

It can be seen from Fig. 2 that, when MISSA is used to solve functions F1–F3, its convergence accuracy and speed are significantly better than those of the other algorithms. When solving functions F4–F5, MISSA has the fastest convergence speed, and its search capability over the entire search space and its local exploration capability are significantly better than those of the other algorithms.

Several algorithms. That is, MISSA has an obvious advantage in the optimization process for the selected test functions. In the following, MISSA is applied to sensor placement optimization and to the corresponding parameter optimization of the BP neural network.

Fig. 2 The iteration curve of each algorithm test

4 Design of the MISSA-BP Algorithm

This study combines MISSA with a BP neural network to establish the MISSA-BP algorithm. The algorithm framework and parameters are designed according to the specific application model. The MISSA-BP algorithm is applied to vibration control of a 20-story steel-structure Benchmark model under seismic excitation; the basic parameters of the model are given in Ref. [15]. The MISSA-BP algorithm can optimize the sensor placement positions under the premise of reducing the number of sensors, and can calculate the control forces of all floors through the sensor feedback information of the selected floors.

4.1 BP Neural Network Settings

The numbers of neuron nodes in the input layer, hidden layer, and output layer of the BP neural network are set to 14, 20, and 20, respectively. The input data are the velocity and displacement information of the floors selected by MISSA relative to the ground, and the output data are the control forces of the target structure at each floor. The BP neural network is trained using the Levenberg-Marquardt algorithm, and the target error is set to 1×10^{-10}.

Fig. 4 Flow diagram of MISSA optimization sensor and BP neural network

Figure 2: Fig. 4 Flow diagram of MISSA optimization sensor and BP neural network

4.2 Setting of the Variables and Objective Function of MISSA

The variables optimized by the algorithm are the combinations of floors on which sensors are to be arranged, X. Since X is discrete data, it must be transformed into continuous data to facilitate the continuity of algorithm optimization. The variables are processed as follows: the value range of each dimension of the variable X is set to $[0.5, 20.4]$, and after taking values, the `round` function in Matlab is used to convert them into integers. The corresponding floor displacement and velocity data are then indexed and used as the input information of the BP neural network. The sparrow population is set to 50, and the maximum number of iterations is set to 100. The objective function F_{Fit} of MISSA is calculated as

$$F_{\mathrm{Fit}} = \sum_{i=1}^{20} \sum_{j=1}^{500} (F_{\mathrm{L}ij} - F_{\mathrm{B}ij})^2 / (20 \times 500) \qquad (9)$$

where F_{L} is the normalized value of the control force calculated by the full-feedback LQR controller; F_{B} is the normalized value of the output control force of the BP neural network; 20 is the number of structural floors; and 500 is the amount of floor-control-force data for each floor.

4.3 Principles and Advantages of the MISSA-BP Algorithm

The MISSA-BP algorithm uses the merit-selection capability of MISSA to directly select a BP neural network whose actual output force is better, that is, whose control effect is better. At the same time, it also optimizes the sensor layout positions, namely the floor combination number. Since the dataset used for BP neural-network training has an important influence on the training and prediction results, the algorithm can also select a relatively good training dataset by selecting the floor combination.

The advantage of the MISSA-BP algorithm is that when the number and positions of sensors need to be changed, the controller of this algorithm can still update the internal neural-network parameters in real time according to the feedback information from the sensors, thereby achieving the current optimal control effect and possessing a certain degree of intelligence $[16-17]$. The structural schematic of the MISSA-BP algorithm is shown in Fig. 3, and the flowchart of MISSA optimizing the sensors and the BP neural network is shown in Fig. 4.

Fig. 3 Schematic diagram of the structure of the MISSA-BP algorithm

Fig. 5 Simulink model of the control system

Figure 3: Fig. 5 Simulink model of the control system

Figure 4 Flow diagram of MISSA-optimized sensors and BP neural network

Fig. 4 Flow diagram of MISSA optimization sensor and BP neural network

5 Numerical Example

5.1 Simulink Model

According to the trial-calculation results, seven floors were selected for the installation of velocity and displacement sensors. In this study, numerical simulation was carried out using the Simulink module in Matlab software. The Simulink model of the control system is shown in Fig. 5. In the figure, W1, W2, B1, and B2 are the BP neural network parameters that need to be optimized by MISSA; the input-layer input data are the floor displacement and velocity information selected by MISSA; the training data used by the BP neural network are the first 500 groups of sampling data for the floor responses and control forces obtained from the Benchmark model under the El Centro wave by the full-feedback classical LQR control algorithm, with a sampling interval of 0.02 s. The MISSA-BP algorithm finally selects the floor combination on which sensors are to be arranged as the 11th, 12th, 16th, 17th, 18th, 19th, and 20th floors.

Figure 5 Simulink model of the control system

Fig. 5 Simulink model of the control system

5.2 Advantage Evaluation of the MISSA-BP Algorithm

To illustrate the necessity of combining MISSA with a BP neural network, the same data set is used, and the velocity and displacement information of the floors selected by MISSA is input into the BP neural network to obtain the control forces for all floors. At the same time, the BP neural network with a training error smaller than that selected by MISSA is introduced into the control system to obtain the control forces for all floors. The above two sets of control forces are compared with the control forces obtained by the MISSA-BP algorithm and those obtained by full-feedback LQR control. To demonstrate the advantages of MISSA in the MISSA-BP algorithm, the control forces calculated by the MISSA-BP algorithm and the SSA-BP algorithm are compared with the results calculated by full-feedback LQR control.

In summary, the numbers of training iterations and final training errors of the three algorithms—MISSA-BP, SSA-BP, and BP neural network—are shown in Table 3; the comparison of the maximum control forces calculated by the three algorithms with those calculated by full-feedback LQR control is shown in Table 4.

From Table 3, it can be seen that, among the three algorithms, the training errors from large to small are, in order, the MISSA-BP algorithm, the SSA-BP algorithm, and the BP neural-network algorithm, and the numbers of training iterations are 422, 486, and 503, respectively. The BP neural-network algorithm has the best training effect, with a training error of 5.20×10^{-10}; next is the SSA-BP algorithm, whose training error is 1.02×10^{-9}; the MISSA-BP algorithm has the poorest training effect, with an error reaching 1.98×10^{-9}. However, it can be seen from Table 4 that, compared with the SSA-BP algorithm and the BP neural network ⋯

Compared with the network algorithm, the maximum story control forces computed by the MISSA-BP algorithm are the closest to those of the classical LQR. From Tables 3 and 4, it can be seen that although the training effect of the MISSA-BP algorithm is not ideal, it requires the fewest training iterations and outputs the optimal control force; that is, it can compute the best story control forces with the lowest training cost, and the actual control effect is better. Therefore, this reflects the necessity of combining MISSA with BP and the superiority of the MISSA-BP algorithm over the SSA-BP algorithm, overcoming the drawback that the BP neural network has poor training performance and unsatisfactory actual control effects.

Table 3 Comparison of training times and final errors of the three algorithms

Tab. 3 Training times and final errors of the three algorithms

Method	MISSA-BP algorithm	SSA-BP algorithm	BP neural network
Training times	422	486	503
Obtained error	1.98×10^{-9}	1.02×10^{-9}	5.20×10^{-10}

Table 4 Maximum control forces calculated by each algorithm under the action of the El Centro wave

Tab. 4 The maximum control force calculated by each algorithm under the action of El Centro wave (Unit: 10^7 N**)**

Algorithm	1	3	5	7	9	11	13	15	17	19
LQR	3.77	2.06	0.89	0.41	0.23	0.27	0.29	0.40	0.34	1.27

Algorithm	1	3	5	7	9	11	13	15	17	19
MISSA-BP algorithm	3.69	2.22	0.86	0.41	0.24	0.25	0.28	0.40	0.33	1.25
SSA-BP algorithm	3.42	2.43	0.72	0.49	0.18	0.19	0.37	0.38	0.39	1.12
BP neural network	8.21	5.02	2.97	1.99	2.22	1.88	2.35	1.87	2.56	4.36

5.3 Evaluation of the Vibration Control Effect of the MISSA-BP Algorithm

The MISSA-BP algorithm is applied to vibration control of the 20-story Benchmark model under the action of the El Centro wave, and the maximum control forces calculated by it, as well as the peak interstory displacement and peak acceleration of the controlled structure, are compared with the calculation results of full-feedback LQR control. The dynamic response and control forces of the controlled structure are shown in Fig. 6.

Fig. 6 Structural response and control force under El Centro

(a) Peak interstory displacement

(b) Peak acceleration

(c) Maximum control force

Fig. 6 Structural response and control force under El Centro

From Fig. 6, it can be seen that the maximum story control forces calculated by the MISSA-BP algorithm using the selected information feedback from 7 stories are almost the same as those calculated by LQR control using feedback from all stories. The control effects of the MISSA-BP algorithm on the peak interstory displacement and peak acceleration of the structure are close to those of LQR control, and for some stories the control effect is even better than that of LQR control.

5.4 Evaluation of the Generalization of the MISSA-BP Algorithm

To verify the generalization of the control of the MISSA-BP algorithm, the sensors are placed respectively on the 11th, 12th, 16th, 17th, 18th, 19th, and 20th stories of the Benchmark model. The Kobe (NS, 1995) wave, with an acceleration peak of 8.18 m/s^2, is selected as the new seismic excitation; its duration is 30 s, and the data sampling step is 0.02 s. The maximum control forces calculated by this algorithm under the Kobe wave are compared with the calculation results of the full-story-feedback LQR; the maximum control force of the controlled structure is shown in Fig. 7.

Fig. 7 Maximum control force of the structure under Kobe

Fig. 7 The peak force of the structure under Kobe

From Fig. 7, it can be seen that, when the Kobe wave is used as the new seismic excitation for the structure,

under these conditions, the MISSA-BP algorithm can still compute, based on limited state feedback information, a control force close to that of full-feedback LQR; therefore, this control algorithm has relatively strong generalization capability.

6 Conclusion

Compared with SSA and the other three classical algorithms, MISSA has an obvious advantage in function solving, indicating that the improvement of the algorithm is effective. The BP neural network selected by MISSA performs better in actual vibration control than a BP neural network with training effects chosen manually, overcoming the shortcomings in BP neural-network training and prediction whereby uncertainty affects the control effect. With sensors arranged on only 7 floors, i.e., under the premise of using limited state feedback, the MISSA-BP algorithm can achieve a control effect very close to that of full-state-feedback LQR control. For the control model after parameter optimization, when a new seismic excitation is input, a control force close to that of full-feedback LQR can still be obtained; that is, the control system has relatively strong adaptability. Moreover, when the number and positions of sensors need to be adjusted, this control algorithm can select in real time an appropriate sensor layout scheme and a BP neural network corresponding to it with good control performance, showing relatively high flexibility.

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